Introduction to Econometrics [EC421]

Spring 2025 Syllabus

Dr. Edward Rubin, Dept. of Economics, University of Oregon

Basics

	Lecture	**Lab**
	Tu. & Th. 12:00p–1:20p	Th. 3:00p–3:50p & Async.
	221 McKenzie Hall	Zoom & Canvas recording
	Edward Rubin	**Emily Arnesen**
	edwardr@uoregon.edu	earnesen@uoregon.edu
	Use "EC421" in email subject.	
	Course page: https://github.com/edrubin/EC421S25	
	edrub.in	emilyarnesen.com
	Tu. 1:30p–3:00p (PLC 530)	We. 3:30p–4:30p (Zoom)
	Get in touch if you cannot make scheduled office hours.	
	Introduction to Econometrics, 5th ed.	
	Mastering 'Metrics: The Path from Cause to Effect	

Email note: We will do our best to respond promptly to your emails. Our responses may be slower over weekends/holidays. There may be times that our responses take up to 48 hours. Please do not repeatedly send the same email.

Materials from previous courses	
https://github.com/edrubin/EC421W25	421, Winter 2025 course on Github
https://github.com/edrubin/EC421W22	421, Winter 2022 course on Github
https://github.com/edrubin/EC421W21	421, Winter 2021 course on Github
https://github.com/edrubin/EC421S20	421, Spring 2020 course on Github
https://github.com/edrubin/EC421W20	421, Winter 2020 course on Github
https://github.com/edrubin/EC421S19	421, Spring 2019 course on Github
https://github.com/edrubin/EC421W19	421, Winter 2019 course on Github

	Synchronous Thursday labs	**Asynchronous Labs**
	4:00p–5:20p (PST), Zoom	Recorded
	Zoom (links on Canvas)	Zoom (links on Canvas)
Lab instructor	**Emily Arnesen**	**Emily Arnesen**
	earnesen@uoregon.edu	earnesen@uoregon.edu

Labs: There are two labs—open for anyone to attend. One lab is synchronous. We will record the synchronous lab and make the videos/materials available for the asynchronous version. You are allowed to attend a lab different from the one you registered for. Some labs may also include assignments.

Recommendations

1. **Be kind**.
2. **Take responsibility** for your own education and try to **learn** as much as you can.
3. **Do your own work**.
4. Develop your **intuition**—*e.g.*, why does regression work in one situation and fail in another?
5. **Learn** `R`. Struggle while you try—and use **Google** to figure things out.
6. Come to **office hours**.[1]
7. **Ask for help early**—don't wait until the end of the term.
8. **Leave enough time to get help** (start assignments/projects early enough to get help with issues).

Course summary

Description: This course aims to prepare economics majors for the demands of real-world applications and for the econometrics required by other 400-level classes. Toward this goal, we will examine the assumptions that underly the econometric and statistical models that you learned in Economics 320 (along with Math 243). These models imposed strong assumptions that are often violated in practice. We will relax these assumptions—replacing them with looser, more palatable assumptions—and derive, build, and estimate the resulting new models. By the end of this course, students should have the ability to statistically examine the bulk of economic issues using econometrics—knowing how to empirically test economic models and knowing the strengths, weaknesses, and assumptions of their chosen route of analysis.

Learning statistical programming is inherent to practicing applied econometrics. Thus, throughout this course we will also teach the statistical programming language `R`.

Prerequisites: This course requires Economics 320 (Introduction to Econometrics)—we assume you are comfortable with the content in the first six chapters of the Dougherty *Introduction to Econometrics* (ItE) textbook.

Software and tools

R: We will use the statistical programming language `R`, and we will use `RStudio` to interact with `R`.

Learning R: will require time and effort, but it is a powerful and versatile tool that is valued by many employers. Put in the requisite effort and time, and you will be rewarded. Computers around the university already have R, but I strongly recommend that you install `R` and `RStudio` on your own computer.

If you are concerned about learning `R`—or want to learn more/quickly—I suggest that you check out the following free, online resources.

- DataCamp's *Introduction to R*

[1] Two related articles from NPR on office hours: *College Students: How to Make Office Hours Less Scary* and *Uncovering A Huge Mystery Of College: Office Hours*.

- TeamLeada's *R Bootcamp*
- Computerworld's *Beginner's guide to R*

The folks at `posit/RStudio` put together a very nice set of resources.

Labs, homework, and exams

Lab: This course includes a lab, which is integral to learning the material in (and passing) this course. For now, we are requesting that you attend the lab for which you registered. The lab includes both general econometrics instruction and computing tips necessary to complete the homework assignments—linking the lecture material to `R`—as well as topics which the lecture may not be cover. **The lab is the best way you can get quick feedback and help in this course.** The GE will also post a video for you to watch before the remote lab meeting/call.

See above for lab times.

Problem Sets

- You will **turn in assignments online via Canvas**. The submission should include your written answers and your figures—and a separate file for your code.
- Assignments will be due approximately every 1–2 weeks.
- In general, we will select 10 questions to grade from each problem set.
- Assignments **must be in your own words**. **Do not copy**.
- See below for **late policy**.

Feel free to work together on the assignments. Unless explicitly stated, **each student is required to write and submit independent answers**. This means that word-for-word copies will not be accepted and will be viewed as academic dishonesty. In other words: You must place answers **in your own words**. **Copying from other people (even if you worked with them) or from previous assignments is considered cheating.** The same policy applies to ChatGPT, Copilot, and any other AI/large-language models: you can use them, but your answers must be in your own words and you must understand the `R` code that you submit.

Late policy

- We accept assignments **up to 48 hours late**, but we **subtract 2 percentage points for each hour it is late.**
- For example, you turn in an assignment 12 hours late and would have received 85%. We subtract $12 \times 2 = 24$ percentage points, meaning you will receive 85% − 24%=61%.
- No exceptions.

Exams

- The **in-class midterm is tentatively planned for 06 May 2025 (during class)**.
- The **in-person final exam will be Friday, 13 June 2025, 8:00a–10:00a**.

We will not offer early or make-up exams. If you cannot take the midterm, we will move its weight to the final. If you cannot take the final, we will predict your final grade using your performance on the other course components (and your classmates' scores) and then subtract 10 percentage points. If you miss both the midterm and the final, you will fail the class.

Grades

Grades for this class will be assigned based on the following assignments: approximately four homework assignments, one midterm exam, and one final exam. Final grades will be determined based on your rank-ordered position within the class (*i.e.*, the course may be curved). You can track your grades for individual assignments on Canvas. The weights for the final grade:

Problem Sets (includes lab assignments)	35%
Midterm Exam	30%
Final Exam	35%

Textbook and other readings

One of the goals of this course is to make you aware of the incredible array of instruction material that is freely available online. I also want to encourage you to be entrepreneurial (key for learning to program).

Econometrics books: There are two recommended textbooks for this course.

1. **Mastering 'Metrics: The Path from Cause to Effect** by Angrist and Pischke (**MM**)
2. **Introduction to Econometrics**, 5th ed. by Christopher Dougherty (**ItE**)

You should be able to purchase these books at the UO Duckstore or on Amazon (you should already have ItE from EC320). I recommend that you read the assigned readings from the textbooks. The texts provide another, complementary perspective on the material that we cover in lecture. The course schedule (farther below) contains suggested readings for each topic.

R books: For learning R, I recommend Garrett Grolemund and Hadley Wickham's ***R* for Data Science**, which is available for free online. Want to go deeper? Check out **Advanced *R*** (Hadley Wickham, again) and **Data Visualization: A practical introduction** (Kieran Healy)—both books are free online.

Honesty and academic integrity

You must do your own work. Do not claim credit for any work other than your own. Cheating or plagiarizing of any sort on any component of this class will result in a failing grade for the term and a report of the offense to the university. Anything you submit with your name must be in your own words. Copying from other sources—including classmates, previous assignments, and websites—is cheating. Please acquaint yourself with the Student Conduct Code.

Accessibility, disruption, and other university policies

UO now hosts a library of policies that should be available via Canvas (or the included links).

Tentative course outline

The table below presents the current plan for the course outline and associated textbook reading assignments. We will occasionally assign papers for you to read for class, lab, or your homework assignments. I will post these papers on Canvas. As the title of this section suggests, the timing and topics on this schedule may change.

Tentative course schedule

Class	Week	Date	Topics	Suggested readings
01	01	04/01	Intro	ItE 1–6
02	01	04/03	Review	
03	02	04/08	Review	ItE 1–6; MM 2
04	02	04/10	Review	ItE 1–7
05	03	04/15	Heteroskedasticity	ItE 7
06	03	04/17	Heteroskedasticity	ItE 7
07	04	04/22	Consistency (and Inconsistency)	ItE pp. 68–75
08	04	04/24	Time Series	ItE 11
09	05	04/29	Time Series	ItE 11
10	05	05/01	Midterm Review	ItE 12
11	06	05/06	**Midterm**	
12	06	05/08	Autocorrelation & Nonstationarity	ItE 12 & 13
13	07	05/13	Autocorrelation & Nonstationarity	ItE 12 & 13
14	07	05/15	Causality	MM 1
15	08	05/20	Causality	MM 1
16	08	05/22	Instrumental Variables	ItE 9; MM 3
17	09	05/27	Instrumental Variables	ItE 9; MM 3
18	09	05/29	Machine Learning or Panel Methods	
19	10	06/03	Machine Learning or Panel Methods	
20	10	06/05	Review	
	11	06/13	**In-class final exam, 8a–10a**	